Journal of Business and Economics, ISSN 2155-7950, USA
January 2017, Volume 9, No. 1, pp. 19-33
DOI: 10.15341/jbe(2155-7950)/01.09.2018/002

http://www.academicstar.us

FRTB: Default Risk Charge (DRC) Model — When is the Internal Model Approach Advantageous? Comparison: Standardized Approach vs. Internal Model Approach*

Andreas Bohn, Michael Buser, Bernhard Kronfellner, Stefan Schneeberger, Stephan Süß
(The Boston Consulting Group GmbH, Germany)

Abstract: In January 2016, the Basel Committee on Banking Supervision (BCBS) issued the final version of the revised minimum capital requirements for market risk, also known as the "Fundamental Review of the Trading Book (FRTB)". The new regulation comes with many changes, one of which is a dedicated Default Risk Charge (DRC). This new capital charge replaces the Incremental Risk Charge (IRC) under Basel 2.5, and its calculation will become mandatory for banks as of 2019, when the new BCBS capital requirements come into effect. The biggest conceptual differences between the DRC and the IRC are that the former is designed to capture only default risk, whereas the latter also captures migration risk, and that equity positions are in the scope of the DRC, whereas they were out of the scope of the IRC.

The biggest methodological differences are that the FRTB prescribes the use of a two-factor default simulation model in the internal model approach for DRC (whereas IRC had no specified number of factors), along with restrictions on the empirical data used to calibrate the model. The new prescriptions in the internal model approach will evoke some methodological questions, implementation options, and regulatory uncertainty across the banking industry.

While banks are preparing for this regulatory framework, we describe a potential model for the DRC in the internal model approach. We compare the results of our model with the standardized approach and derive suggestions for the methodological choices a bank is facing. Our findings suggest that the question of whether to use the standardized approach or the internal model approach strongly depends on the structure of the trading book portfolio. In some cases the standardized approach is less capital-intensive than the internal model approach.

Key words: banking regulation; market risk; fundamental review of the trading book; default risk charge
JEL codes: G13, G18, C51

1. Introduction

In January 2016, the Basel Committee on Banking Supervision (BCBS) issued the final version of the revised minimum capital requirements for market risk, also known as the "Fundamental Review of the Trading

* Article was first published in German in Risiko Manager 3/2017, this is an abridged translation.

Andreas Bohn, Dr., The Boston Consulting Group GmbH; research areas/interests: market risk, liquidity risk, counterparty credit risk. E-mail: bohn.andreas@bcg.com.

Book (FRTB)". The minimum capital requirements for market risk can be determined either by the standardized approach or by the internal model approach, provided that the bank obtains approval on a desk level.

If a bank wants to obtain approval for application of the internal model approach for any of its trading desks, it is mandatory to also apply an internal Model for the Default Risk Charge. The default risk charge (DRC) replaces the incremental risk charge (IRC) in Basel 2.5 and continues to be one of the most complex and challenging components of the new market risk framework for banks. The DRC reduces degrees of freedom/variations compared to IRC such as: (a) the number of risk factors is restricted to two types systematic factors in DRC; (b) specific guidelines for the measurement of asset correlations are provided; (c) PD and LGD need to be taken from the internal Basel models (where these exist), etc.

Figure 1 shows the building blocks of the current (Basel 2.5) and the new future market risk framework (FRTB) and illustrates the model changes, for both the standardized and the advanced approach. In particular, the incremental risk charge (IRC) under Basel 2.5 will be replaced by the default risk charge DRC, which is the focus of this paper.

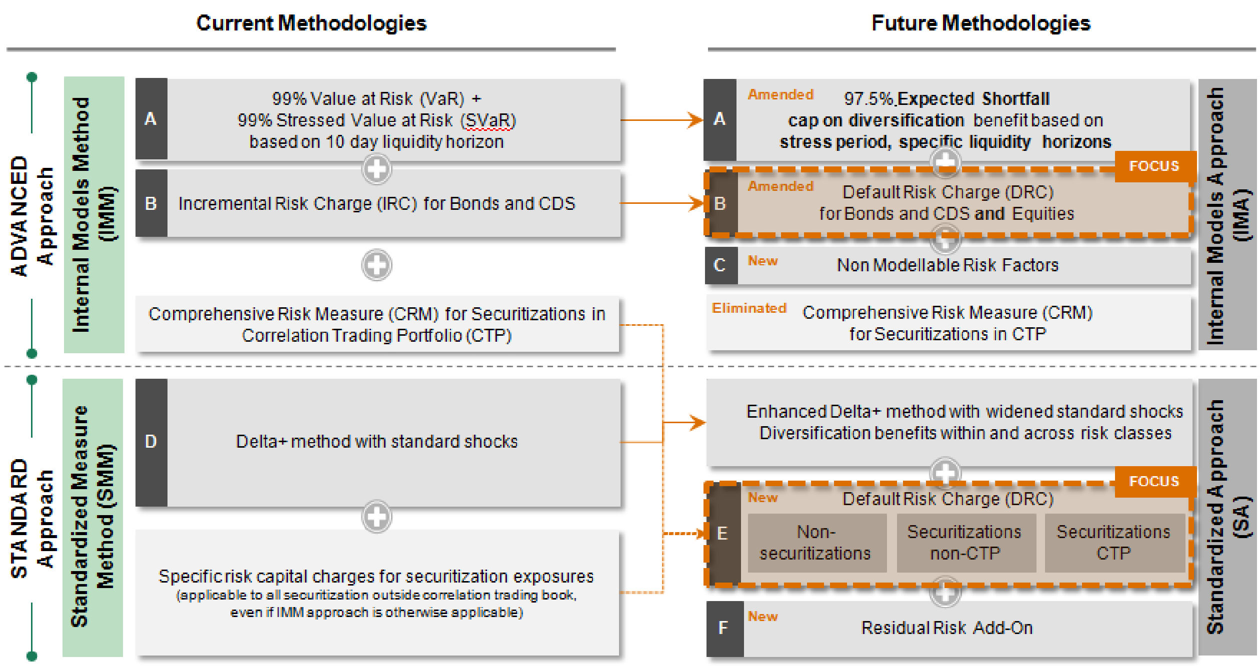

Figure 1 Methodological Changes between Basel 2.5 and FRTB for Both the Advanced and the Standardized Approach

Source: BCG analysis, FRTB QIS 4 from July 2015 (BCBS), Final FRTB publication: "Minimum capital requirement for market risk" from January 2016 (BCBS).

In the standardized approach, the Basel Committee on Banking Supervision explicitly describes the DRC model by prescribing fixed equations and factors that each bank in the standard approach has to use. In contrast, in the internal model approach the Basel Committee for Banking Supervision only describes the mechanisms that need to be incorporated in the DRC model. For instance, the Basel Committee prescribes the use of a two-factor default simulation model to capture correlated defaults, where the data used to calibrate the model must be either annual equity or credit spread correlation data that covers a period of ten years (including a period of significant stress), and the DRC is defined to be the 99.9% quantile of the simulated loss distribution. The full regulatory requirements are described in Section 0 below. On the one hand, the vague prescriptions give more methodological freedom to banks to tailor a DRC model to their specific business environment and operating characteristics. On the other hand, this bears a certain regulatory uncertainty, as local regulators need to approve the developed DRC model on a trading desk level.

The purpose of this paper is to compare the standardized and the internal model approaches to DRC, and to identify conditions under which the internal model approach tends to outperform the standardized approach (and vice versa). To this end, we implement a DRC model that follows the basic framework of Wilkens and Predescu (2016). In particular, the default correlation dynamics are described by a structural factor model in the spirit of Merton (1974) and Vasicek (1987, 2002), which is a widely used workhorse model for default risk. We compare the results of our model with the standardized approach for DRC, where we compare the sensitivity of the default risk charge and its capital consumption along various changing parameters. We find that the choice of standardized approach versus internal model approach strongly depends on the structure of the portfolio (e.g., the size of the portfolio, the rating of the portfolio positions, etc.). For instance, in some of our cases, the standardized approach requires three times as much capital as the internal model approach, and vice versa. Our results are qualitatively summarized in Figure 2 below.

	Description	Relatively lower capital charge	
		SA	IMA
A Portfolio Size	Number of different obligors / portfolio positions	Small	Large
B Portfolio Concen-tration	Degree of diversification among various portfolio positions	Concentrated	Diversified
C Portfolio Correlation	Average correlation between different portfolio positions	Positive	Negative
D Distribution of PDs	PDs above 0,1% directly hit the 99,9% percentile VaR	Few top-rated positions	Many top-rated positions
E Portfolio Quality	Quality / rating of the portfolio positions	Stable portfolio quality	Volatile portfolio quality
F Portfolio composition	Portfolio composition of equity and bonds	Both approaches benefit from short equity positions offsetting long bond positions	

Figure 2 Comparison of SA-DRC and IMA-DRC in Terms of Portfolio Characteristics

Source: BCG analysis

2. Related Literature

The final version of the FRTB was issued in 2016, and so the relevant literature is scarce. Our modeling approach follows the work of Wilkens and Predescu (2016), who provide a general framework for the default risk charge. We deviate from their setup by using a principal components analysis to extract latent systematic factors from the asset correlation matrix to describe joint asset dynamics, instead of constructing systematic factors from observed financial time series. The default correlation mechanism in the model is in the spirit of Merton (1974) and Vasicek (1987, 2002).

Laurent et al. (2016) analyze the theoretical foundations of the FRTB prescribed DRC model rules. In

particular, they investigate the practical implications of the two-factor and correlation calibration constraints through numerical applications.
The way we model basis risk follows an idea outlined in BCBS d305 (2015): Fundamental review of the trading book: outstanding issues.

3. Regulatory Background

The new standard defines "default risk" as the risk of direct loss due to an obligor's default as well as the potential for indirect losses that may arise from a default event.

The regulatory requirements can be categorized according to the following six dimensions. In the following, we highlight the main criteria of the new standard using these dimensions via the relevant sections from BCBS d352, with additional elaborations where useful.

3.1 Definition and Calculation of Risk Metric

- Default Risk: Direct loss due to a default as well as the potential indirect losses
- Metric: Default risk must be measured using a VaR (Value at Risk) model.
- Factors: Two types of systematic risk factors.
- Confidence: One-tail, 99.9 percentile confidence level.
- Liquidity Horizon: VaR calculation must be based on a one-year time horizon. Banks have the discretion to apply a minimum liquidity horizon of 60 days to the determination of DRC for equity sub-portfolios.

3.2 Included Positions and Scope

- Instruments: All positions subject to the market risk framework that have default risk as defined in paragraph 186(a) BCBS d352, with the exception of those positions subject to standardized charges are subject to the default risk charge model must be included. Therefore, sovereign exposures (including those denominated in the sovereign's domestic currency), equity positions and defaulted debt positions must be included in the model. (Note: Equity is new in the scope of the DRC, and was not within the scope of the IRC).
- Frequency: The DRC calculation must be done weekly.
- Stability: The capital requirement is the greater of: (1) The average of the DRC model measures over the previous 12 weeks; or (2) the most recent DRC model measure.
- Loss amount: For each and every position, an incremental loss amount relative to the current valuation "t", in the event that the obligor of the position defaults. I.e., losses must be assessed from the perspective of the incremental loss from default in excess of the mark-to-market losses already taken into account in the current valuation.
- Losses on equity: Default of an issuer must be modeled as resulting in the equity price dropping to zero.
- Modeling options: The model must reflect the non-linear impact of options and other positions with material non-linear behavior. In the case of equity derivative positions with multiple underlyings, simplified modeling approaches (for example, modeling approaches that rely solely on individual jump-to-default sensitivities to estimate losses when multiple underlyings default) may be applied (subject to supervisory approval).
- Concentration: The model must reflect the effect of issuer and market concentrations, as well as concentrations that can arise within and across product classes during stressed conditions.

- Position mismatch: The model must capture any material mismatch between a position and its hedge. With respect to default risk within the one-year capital horizon, the model must account for the risk in the timing of defaults to capture the relative risk from the maturity mismatch of long and short positions of less than one year's maturity.
- Netting same obligor: The model may reflect netting of long and short exposures to the same obligor, and if such exposures span different instruments with exposure to the same obligor, the effect of the netting must account for different losses in the different instruments.
- Basis Risk: The basis risk between long and short exposures of different obligors must be modeled explicitly. The potential for offsetting default risk among long and short exposures across different obligors must be included through the modeling of defaults. The pre-netting of positions before input into the model other than positions of the same obligor with same maturity and same seniority is not allowed.

3.3 Requirements for the Estimation of PDs

- Granularity: Default risk must be measured for each obligor.
- Historical estimation: PDs must be measured based on historical default data including both formal default events and price declines equivalent to default losses. Where possible, this data should be based on publicly traded securities over a complete economic cycle. The minimum historical observation period for calibration purposes is five years (not part of our model).
- IRB approach usage: Where an institution has approved PD estimates as part of the IRB approach, this data must be used. Where such estimates do not exist, or the supervisor determines that they are not sufficiently robust, PDs must be computed using a methodology consistent with the IRB methodology unless otherwise specified below (not part of our model).
- External sources: PDs provided by external sources may also be used by institutions, provided they can be shown to be relevant for the bank's portfolio. (Market Implied PDs: PDs implied from market prices are not acceptable unless they are corrected to obtain an objective probability of default. Risk neutral PDs should not be used as estimates of observed (historical) PDs (not part of our model).
- Floor: PDs are subject to a floor of 0.03%.
- Hierarchy: Banks must establish a hierarchy ranking their preferred sources for PDs, in order to avoid the cherry-picking of parameters.

3.4 Requirements for the Estimation of LGDs

- Usage of IRB LGDs: Where an institution has approved LGD estimates as part of the IRB approach, this data must be used. Where such estimates do not exist, or the supervisor determines that they are not sufficiently robust, LGDs must be computed using a methodology consistent with the IRB methodology unless otherwise specified below.
- Derivation of losses: LGDs must be determined from a market perspective, based on a position's current market value less the position's expected market value subsequent to default. The LGD should reflect the type and seniority of the position and cannot be less than zero.
- Empirical basis: LGDs must be based on an amount of historical data that is sufficient to derive robust, accurate estimates.
- Market implied LGDs: LGDs provided by external sources may also be used by institutions, provided they can be shown to be relevant to the bank's portfolio.

- Granularity: These loss estimates must reflect the economic cycle; for example, the model must incorporate the dependence of the recovery on the systemic risk factors.
- Floor: Banks must establish a hierarchy, ranking their preferred sources for LGDs, in order to avoid the cherry-picking of parameters.

3.5 Requirements for Default Correlations

- Calibration: Default correlations must be based on credit spreads or on listed equity prices. Banks must have clear policies and procedures that describe the correlation calibration process, documenting in particular in which cases credit spreads or equity prices are used.
- Time series: Default correlations must be based on data covering a period of 10 years. The horizon must include a period of stress.
- Liquidity horizon: The estimation must be based on a one-year liquidity horizon.
- Underlying data: The default risk charge model must recognize the impact of correlations between defaults among obligors, including the effect on correlations of periods of stress. (1) These correlations must be based on objective data and not chosen in an opportunistic way where a higher correlation is used for portfolios with a mix of long and short positions and a low correlation used for portfolios with only long exposures. (2) A bank must validate that its modeling approach for these correlations is appropriate for its portfolio, including the choice and weights of its systematic risk factors. A bank must document its modeling approach and the period of time used to calibrate the model.
- Basis risks: Firms need to reflect all significant basis risks in recognizing these correlations, including, for example, maturity mismatches, internal or external ratings, vintage etc.

3.6 Back Testing and Approval

- Back testing: Owing to the high confidence standard and long capital horizon of the Default Risk Charge (DRC), robust direct validation of the DRC model through standard back testing methods at the 99.9%/one-year soundness standard will not be possible. Accordingly, validation of a DRC model necessarily must rely more heavily on indirect methods including but not limited to stress tests, sensitivity analyses and scenario analyses, to assess its qualitative and quantitative reasonableness, particularly with regard to the model’s treatment of concentrations. Given the nature of the DRC soundness standard, such tests must not be limited to the range of events experienced historically. The validation of a DRC model represents an ongoing process in which supervisors and firms jointly determine the exact set of validation procedures to be employed.
- Benchmarks: Firms should strive to develop relevant internal modeling benchmarks to assess the overall accuracy of their DRC models.
- Desk-by desk-approval: Due to the unique relationship between credit spread and default risk, banks must seek approval for each desk with exposure to these risks, both for credit spread risk and default risk. Desks which do not receive approval will be deemed ineligible for internal modeling standards and be subject to the standardized capital framework.

4. Our Model

We build our model along the requirements mentioned above. However, as outlined in the Introduction, the DRC model in the internal model approach leaves a high degree of freedom to the banks and, thus, to its local regulators. In other words, a DRC model could differ from bank to bank, depending of the methodological choices. Nevertheless, all DRC models need to have in common the follow elements as displayed in Figure 3.

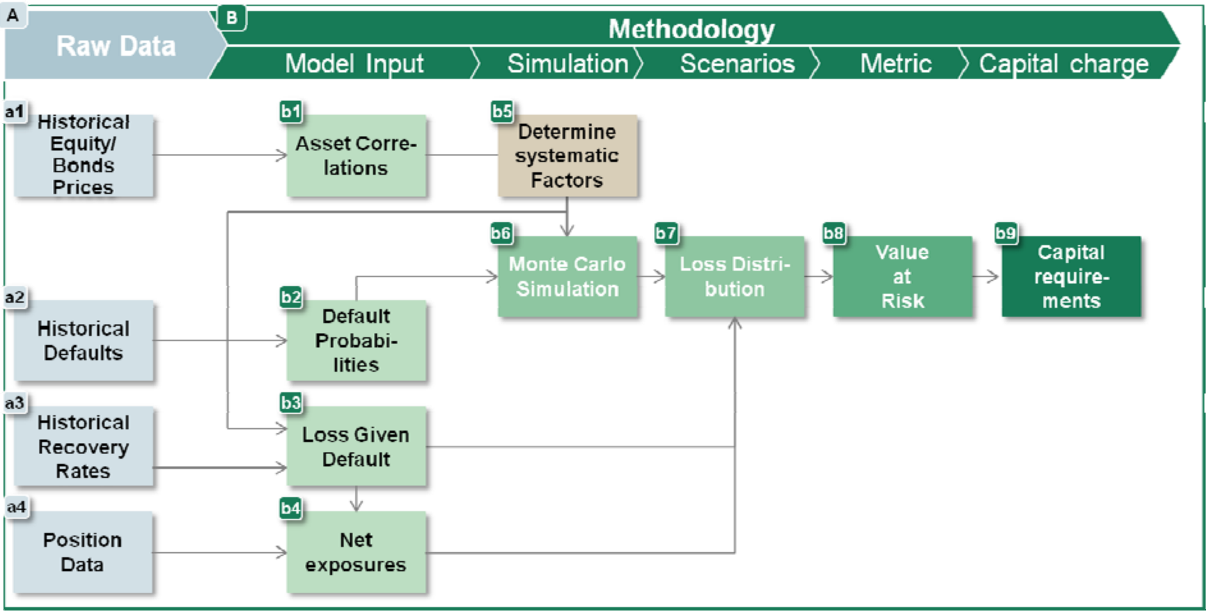

Figure 3 Model Overview

Source: BCG analysis

We use the proposed DRC modeling framework of Wilkens and Predescu (2016) and extend resp. modify their approach along several dimensions. The model that we set up should be interpreted as a basic prototype that can be used to shed light on DRC-related questions for a given portfolio (e.g., will the internal models or the standardized approach be more appropriate for the portfolio at hand). The model can also serve as a starting point to develop a full-fledged DRC-model that is tailored to a bank's characteristics and that can be used to seek regulatory approval as an internal DRC model.

In the next paragraphs we go through the individual model components in Exhibit 6 and describe them accordingly.

a1. Historical equity/CDS prices: We use historical equity/CDS prices for the estimation of asset correlations (50 stocks & 125 CDSs from 2011-2016). Our model can also handle credit spreads instead of CDS spread[1]. A full-fledged DRC project would include the validation of the regulatory compliance of the data used for model calibration. For our prototype, we have considered equities, covered bonds and senior/subordinated debt. Our model can handle more complex products, where a product-specific implementation has to be developed. Our limited data set is meant to focus on the basic workings of the model, while separating out effects from the estimation of a large covariance matrix.

a2/b2. Historical defaults and default probability: In the absence of PDs derived from IRBA (internal rating based approach), we consider historical default rates from Standard and Poor's, covering the 1981 to 2012 window. We use these historical default rates as proxies for IRBA-PDs, which have to be used in case a bank has

[1] Note that observed bond prices (or spreads) are not suitable to determine asset correlations, as they contain an interest rate component that should not be taken into account. Depending on the underlying assumptions on interest rates, synthetically derived bond prices from credit spreads might be used.

an approved IRBA process to calculate PDs. Note that the historic PDs (as well as IRBA-PDs) are significantly smaller than the SA-PDs prescribed in the standardized approach. In line with the approach of Basel, we group rating sub-categories (e.g., AA+, AA, AA-) into single rating buckets (e.g., AA) with a corresponding single PD — for a refinement of the prototype, this needs to be replaced by PD per sub-category.

a3/b3. Historical recovery rates and LGDs: According to the Basel rules, default loss estimates must "reflect the economic cycle; for example, the model must incorporate the dependence of the recovery on the systemic risk factors" (BCBS d352, paragraph 186(m)). To this end, we propose a flexible copula-based stochastic LGD model that links an obligor's recovery rate and the systematic factors that drive the correlated default dynamics in our simulation model. We use a Gaussian copula as default, but an arbitrary copula function can be used instead. As empirical data input for our LGD model we use historically-observed recovery rates from Centerstate Bank per industry sector, covering the 1981 to 2012 window. We treat these industry-specific LGD rates as expected rates and perturb those values with random draws that we obtain from our copula model to obtain realized LGD rates that we then use in the subsequent DRC calculations.

a4/b4. Position data and net exposure: We compute the net asset exposures (EaD) with consideration of the seniority of positions: (1) Netting long/short positions of same obligor and (2) Waterfall principal: short positions are netted with more senior long positions, but not vice versa. Netting short and long positions gives an entry point to explicitly model basis risk.

b1. Asset correlation: We use a principal components analysis (PCA) of the joint correlation matrix (equities, CDSs) to identify two significant factors, as prescribed by the Basel rules. In order to do so we proceed in two steps:

First, for a given portfolio of stocks and CDSs, we compute the joint correlation matrix of these assets.
Second, we perform a Principal Components Analysis (PCA) of the joint correlation matrix where we determine the factor loadings for the first two principal components (factors) that jointly drive the time series dynamics of equities and CDSs. These factor loadings are given by the (normalized) eigenvectors associated with the two largest eigenvalues of the covariance matrix. The magnitudes of the eigenvalues confirm their statistical significance.

Note that for large portfolios, the correlation matrix becomes numerically intractable[2]. Large financial institutions facing such a problem could split the correlation matrix into more separated matrices and combine the factors in a third step. Since we want to focus on the comparison between IMA-DRC and SA-DRC in a "laboratory" environment, we only use a small sample size to avoid such numerical issues.

b5. Determine systematic factors: Equity and CDS returns determine the factor sensitivities for each asset, which are given by the corresponding factor loadings from the PCA for this asset[3].

Before we compute these factor loadings, we normalize the return time series of all assets to have mean zero and variance one. This normalization gives us a natural choice for mean and variance (namely zero and one) for the random variables that we use to model the two systematic factors in our simulation procedure, which we denote by Z_1 and Z_2. We find that the factor loadings for the first factor are of a similar magnitude for all assets, whereas the loadings for the second factor correlate negatively with the market size of an asset. Hence, to give these two factors a concrete interpretation, we can view Z_1 and Z_2 as market and size factor, respectively.

[2] Since the matrix size grows quadratically in the number of assets, an "out-of-memory" problem can occur. In particular, inverting the matrix for the PCA can become problematic.
[3] In Figures 4 and 5 below, we denote the two factor sensitivities of asset *i* by β_{i1} and β_{i2}, respectively.

Basis risk: To capture basis risk in a portfolio we follow a suggestion outlined in a consultative BCBS document on FRTB[4]. The idea underlying what is called the "Committee's baseline method" therein, to capture basis risk, is to rescale the individual asset sensitivities to the risk factors within properly defined asset buckets. We formalize this approach in the following way. Recall that our model has two systematic factors, which we denote by Z_1 and Z_2. For concreteness, Z_1 and Z_2 could be a market factor and a size factor, respectively. We can then define four buckets: "long Z_1", "short Z_1", "long Z_2" and "short Z_2". Correspondingly, we decompose each net asset exposure into two factor specific components, according to their respective (squared) factor loadings. Recall that the squared factor loadings represent the fraction of the total variance of an assets' return that is explained by the respective factors. In the next step we determine which exposure direction — long or short — needs to be scaled down. We do this for each factor by determining whether the overall portfolio is long or short in the corresponding factor. If the overall net exposure of the portfolio for a given factor is positive (negative), we scale down the negative (positive) of the individual factor specific components by a factor proportional to the associated factor sensitivity of the exposure for this factor[5]. This rescaling captures the risk of an imperfect hedge (e.g., a short exposure to Z_1 offsets a (larger) long exposure to the same factor only to a limited extent). By construction, this approach to model basis risk is flexible and general and its usage is not restricted to certain asset configurations.

b6. Monte Carlo Simulation: The way we simulate correlated defaults in the spirit of Merton (1987). For each obligor *i*, we introduce a standard Gaussian random variable X_i (i.e., a random variable with zero mean, variance one). We shift the mean of X_i up by a constant[6] to reflect the rating class of this obligor (a better rating class means a higher mean). In this way we capture the marginal default probability of obligor *i*. This mechanism is illustrated in Figure 4.

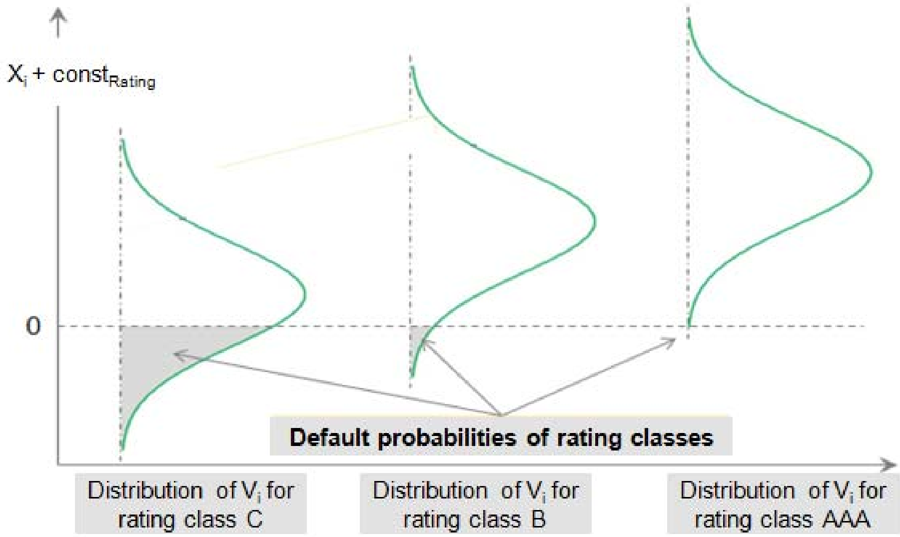

Figure 4 Simulation of Defaults (Without Systematic Factors)

4 See BCBS d305d; Consultative Document: "Fundamental review of the trading book: outstanding issues", Section 2.2.

5 For instance, if the overall portfolio is long in Z_1, we scale down each individual Z_1–specific short exposure by a factor $(1 - 0.05\,|\beta_{i1}|)$, while individual Z –specific long exposures are not rescaled. The choice of 0.05 in the scaling factor stems from the BCBS baseline method, where a scaling factor of 0.95 is used for a single risk factor.

6 In our model, $Const_{rating}$ equals $N^{-1}(PD_i)$, where N^{-1} is the quantile function of the standard Gaussian distribution and PD_i is the marginal default probability of obligor *i*.

The default correlation comes into our model through the systematic factors. The two systematic factors Z_1 and Z_2 impact all obligors, and thus, make defaults correlated. The impact of the systematic factors on an obligor is given by the corresponding factor loadings[3]. We model the systematic factors Z_1 and Z_2 with standard Gaussian random variables. We then simulate from these distributions and, for each simulation run, determine for each obligor whether a default occurs or not[7]. This mechanism is illustrated in Figure 5.

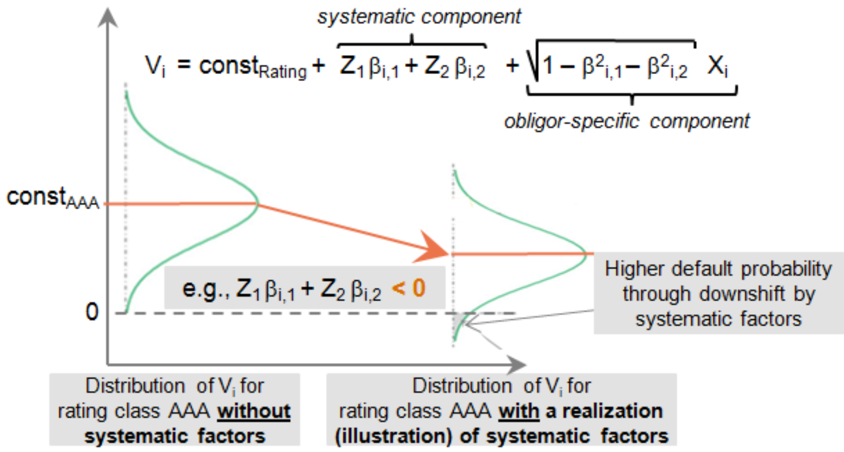

Figure 5 Effect of the Systematic Factors Z_1, Z_2 on the Simulation of Correlated Factors

b7/b8. Loss Distribution: To generate a single scenario with correlated defaults, we simulate the random variables Z_1 and Z_2 (i.e., the two systematic factors in our model), and, for each obligor *i*, the random variable X_i. With these numbers, we determine the default status of each obligor in the current scenario (as described on the previous slide). For each defaulted obligor, we consider all corresponding exposures to this obligor as defaulted. We simulate a large number of scenarios (e.g., N = 100,000) to obtain a reliable estimate of the loss distribution and, subsequently, the associated DRC. For each simulated scenario, we determine a corresponding portfolio loss to obtain a portfolio loss distribution (see one example in Figure 6). This distribution represents the hypothetical losses due to (correlated) defaults in the portfolio. From this distribution we compute the default risk charge.

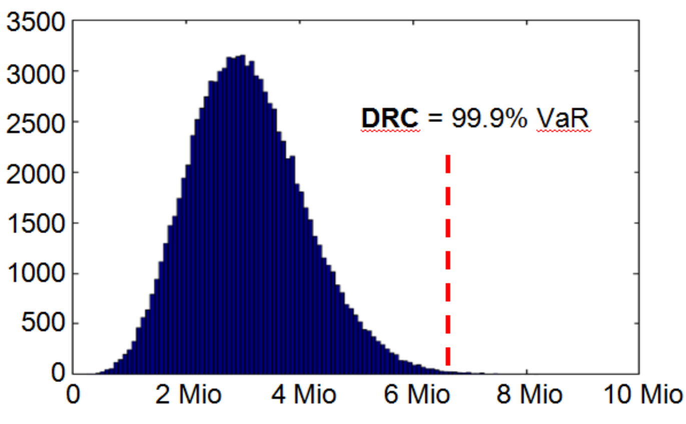

Figure 6 Distribution of Portfolio Losses with Correlated Defaults (Illustrative Example)

[7] Specifically, in each simulation run, we make a draw from the distribution of Z_1 and Z_2, and, for each obligor individually, a draw from the distribution of X_i. We then combine these draws into the variable $V_i = const_{Rating} + Z_1\beta_{i,1} + Z_2\beta_{i,2} + \sqrt{1-\beta_{i,1}^2-\beta_{i,2}^2}\,X_i$. We treat obligor i as defaulted if the value of V_i is negative.

According to the Basel rules, the DRC (Default Risk Charge) of the IMA approach is determined by the 99.9% percentile VaR (Value at Risk) of the simulated loss distribution, as indicated in Figure 7.

b9. DRC capital requirement: Capital charge is the maximum of the average of the DRC model over the previous 12 weeks and the last DRC measure.

Overall, note that to achieve faster model convergence, different variance reduction techniques can be used such as importance sampling, stratified sampling, and antithetic sampling.

5. Choices and Challenges

Banks face the holistic choice whether to use the standardized or the internal approach for market risk. One aspect of this decision is the DRC, and our comparison between IMA-DRC and SA-DRC can serve as an input to this decision process. Banks that think about implementing an internal DRC model are facing a range of choices. There is no single answer to the question of how to implement the DRC in the most efficient and capital-optimizing way. We see four dimensions to optimize the implementation of a DRC model:

a) **Input/data choices**: decision on used data and parameters on observed, simulated, calculated figures.
b) **Numerical choices**: decision on numerical techniques to be installed to cope with large data sets; especially large portfolios can cause difficulties in calculation.
c) **Software choices**: decision on used software packages for a short-term prototype (also to take strategic decisions) and long-term IT implementation.
d) **Model choices**: decision on the usage of DRC in standard or in internal model approach. The choice, as we will point out in the next chapter, strongly depends on the structure of the portfolio (size, concentration, correlation, distribution of PDs, etc.).

The objective of our model (and the implemented BCG prototype) is to identify the levers and drivers of the DRC model for a given portfolio. This pre-implementation analysis gives, for instance, an indication whether to focus rather on a standard or on an internal model for a further DRC implementation.

6. Results of a Comparison of SA and IMA

We compare the results of our model with the standard approach for DRC. Using a selected set of empirical data (as described in the Appendix), we compare the sensitivity of the default risk charge and its capital consumption along various changing parameters. Specifically, we vary portfolio size, portfolio concentration, portfolio correlation, distribution of PDs, portfolio quality, and portfolio composition. We find that the choice of standard approach versus internal model approach strongly depends on the structure of the portfolio. In some of our cases the standard approach is up to three times as capital intensive as the internal model approach, and vice versa.

Our results can be briefly summarized as follows (each paragraph refers to a specific parameter that we vary).

a) Portfolio size:

Result: For a large portfolio (i.e., with many obligors), IMA-DRC tends to yield a lower capital charge than SA-DRC.

Explanation: As the standardized approach does not capture explicit correlations, the further increase in the number of positions does not reduce the capital charge. IMA-DRC is decreasing, because of the incorporated correlation model.

b) Portfolio concentration:

Result: For portfolios with low concentration in positions rated ~BBB or worse, IMA-DRC tends to perform better than SA-DRC.

Explanation: A large portfolio position with IMA-PD >= 0.1% is fully reflected in the 99.9% VaR capital charge (since it defaults in the "worst" 0.1%). SA-DRC, in contrast, is based on an "average" loss calculation, which is less sensitive to tail events.

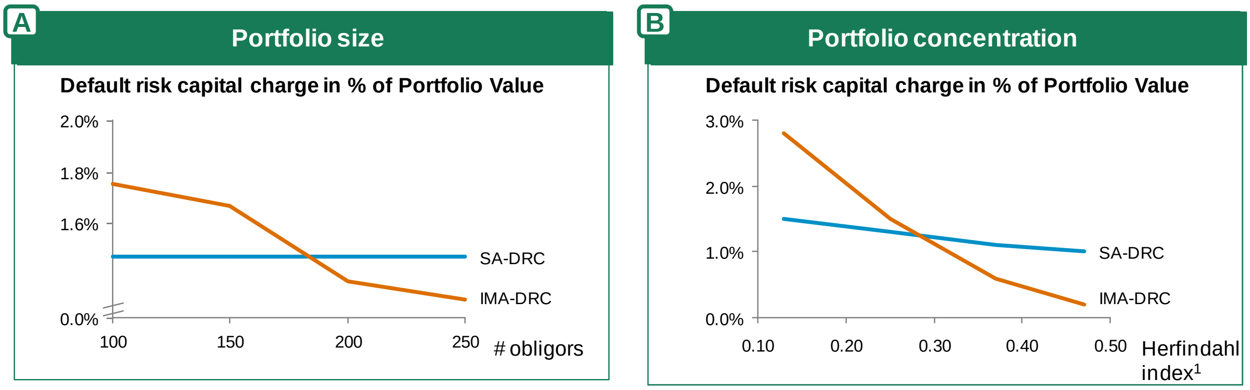

Figure 7 Results of Simulation 1/3 (Default Risk Capital Charge in % of Portfolio Value)

c) Portfolio correlation:

Result: For a non-directional portfolio, i.e., with low or negative correlation, IMA-DRC is better.

Explanation: SA-DRC does not capture correlation, thus a reduction in the average asset correlation does not reduce the capital charge. IMA-DRC is decreasing, because of the incorporated correlation model.

d) Distribution of PDs:

Result: IMA-DRC is suited for portfolios with many (granular) top-rated positions.

Explanation: IMA-DRC is sensitive to default probabilities >= 0.1%, e.g., a rating shift of AA positions (IMA-PD = 0.03%) to BBB positions (IMA-PD = 0.23%) impacts IMA-DRC more than SA-DRC.

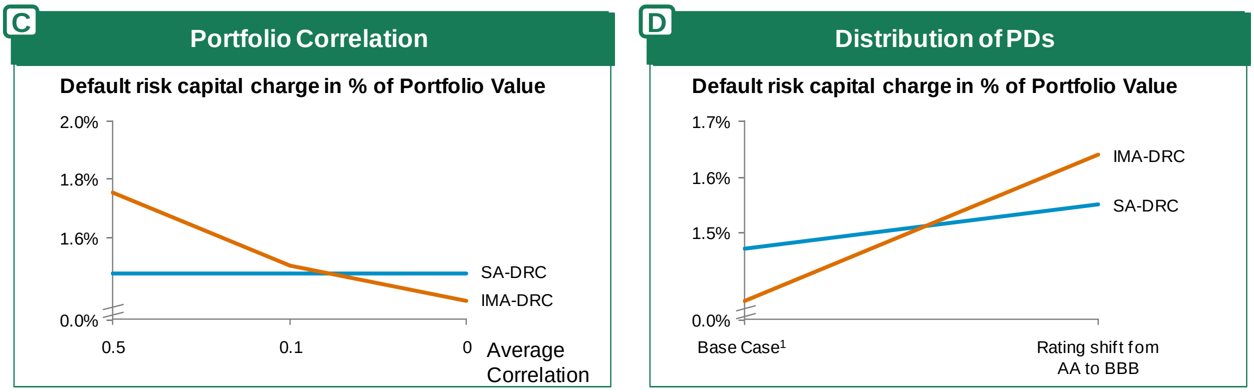

Figure 8 Results of Simulation 2/3 (Default Risk Capital Charge in % of Portfolio Value)

e) Portfolio quality:

Result: For a granular portfolio, IMA-DRC tends to be less sensitive to rating fluctuations (e.g., over the business cycle) than SA-DRC.

Explanation: For a given (granular) portfolio, we consider a general rating deterioration, i.e., a rating deterioration of one notch for each position. We find that IMA-DRC is less sensitive to a general rating deterioration than SA-DRC.

f) Portfolio composition (equities and bonds):

Result: Both IMA-DRC and SA-DRC benefit from short equity positions offsetting long bond positions.

Explanation: We consider a portfolio of 100 obligors with long/short bond and equity positions for each obligor. FRTB prescribes that a senior position cannot hedge a junior position: e.g., a long equity position cannot be hedged by shorting bonds ("waterfall principle").

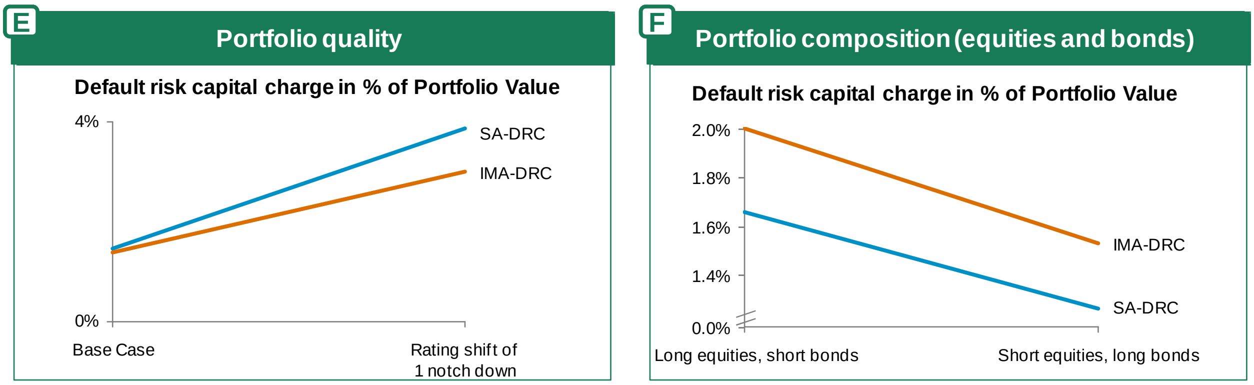

Figure 9 Results of Simulation 3/3 (Default Risk Capital Charge in % of Portfolio Value)

7. Discussion of Our Results

The comparison between the two approaches (SA-DRC and IMA-DRC) does not provide a clear answer to the question as to which approach is preferable over the other. SA-DRC applies prescribed and rating-dependent weights to each position to compute portfolio losses. These fixed weights put SA-DRC at a clear disadvantage compared to historically observed default frequencies. Therefore, IMA-DRC tends to have an advantage, in particular for positions with average (or above) ratings. Another fact that is clearly detrimental for SA-DRC, relative to IMA-DRC, is the prescribed asymmetric offsetting of long and short positions, which is unfavorable for the bank. In particular, highly diversified portfolios are favored by IMA-DRC, relative to SA-DRC. In the previous section, we saw that in SA-DRC in particular, a rating shift "at the top" (d), a change of the portfolio quality (e), and a change of the portfolio composition (f) have strong implications on capital requirements, whereas a change in the portfolio size (a), the portfolio concentration (b), or the portfolio correlation (c) have less pronounced effects.

Nevertheless, due to its computational simplicity SA-DRC exhibits a higher robustness with respect to portfolio composition and obligor's default correlations. This is a direct consequence of the value-at-risk approach of IMA-DRC, which is defined as the 99.9% quantile of the loss distribution and is thus very sensitive to extreme outliers. As a consequence, the result of IMA-DRC is very sensitive to concentration risk, especially in the tail of the overall portfolio loss distribution. Additionally, the value-at-risk is implicitly defined through the general form of the portfolio loss distribution. Besides its variance, which is largely determined by the default probabilities and thus the ratings of the portfolio positions, the third central moment (skewness) describes the asymmetry of the loss distribution, which can increase (or decrease) the value-at-risk. A skewed portfolio loss distribution is in particular generated by large asset correlations in connection with high LGDs. Additional factors that influence the skewness, and thus the general form, of the loss distribution are, e.g., the skewness of the LGD distribution, the distribution of PDs via the rating classes, the choice of copula model to describe PDs and LGDs, and also the skewness of exposures via, e.g., concentration risks.

8. Conclusion

The new rules on a trading book, which are expected to lead to a new Capital Requirement Directive V (CRD V) from the European Commission, cause multidimensional challenges to all banks. If a bank wants to obtain approval for application of the internal model approach for any of its trading desks, an internal model for default risk charge must be applied.

We outline the main options in implementing a DRC model and investigate the choice between standardized approach and internal model approach. Our findings suggest that the internal model approach is not necessarily more capital-efficient than the standardized approach. The default risk capital charge strongly depends on the bank-specific structure of the portfolio. A bank-wide decision (i.e., for all desks) to either use the standardized approach or the internal approach can be highly inefficient in terms of implementation complexity and capital efficiency. Hence, it is strongly recommended that the bank and portfolio-specific drivers (on desk-level) of the DRC be analyzed with a prototype model like one presented above.

The modeling framework that we use is only one potential approach to interpret the regulatory text. As our results indicate, the structure of a bank's trading book will have a strong influence on whether IMA-DRC or SA-DRC will be the preferable alternative from a capital perspective. Hence, further analysis along a bank's specific portfolio characteristics is required to provide an answer to this question. In particular, a thorough investigation of the relevant parameters and characteristics of a bank’s trading book is required to build a full-fledged DRC-model that would obtain regulatory approval.

References

BCBS d305 (February 2015). “Fundamental review of the trading book: outstanding issues”, Issued for comment by 20.

BCBS d352 notes (January 2016). “Explanatory note on the revised minimum capital requirements for market risk”, BIS.

Laurent J. P., Sestier M. and Thomas S. (December 2016). “Trading book and credit risk: How fundamental is the Basel review”, *Journal of Banking and Finance*, Vol. 73, pp. 211-223.

Merton R. C. (1974). “On the pricing of corporate debt: The risk structure of interest rates”, *The Journal of Finance*, Vol. 29, No. 2, pp. 449-470.

Vasicek O. (1987). “Probability of loss on loan portfolio”, *KMV Corporation*, Vol. 12, No. 6.

Wilkens S. and Predescu M. (2016). “Default risk charge (DRC): Modeling framework for the ‘basel’ risk measure”, *Journal of Risk*, available online at: https://ssrn.com/abstract=2638415.

Appendix Data Description

A detailed description of the data used to construct sample portfolios. BCG's DRC-Prototype could easily incorporate any other (bank-specific) portfolio.

Obligors	Equities: Constructed from Euro Stoxx 50 Bonds: Constructed from iTraxx Europe
Return (average monthly return)	Average Return for Equities: 0.56% Average Return for Bonds: 0.03%
Volatility (average standard deviation of monthly returns)	Average St.dev. for Equities: 0.08 Average St.dev. for Bonds: 0.01
Correlation	Among Equities: 0.51 Among Bonds: 0.57 Among Bonds/Equities: 0.39
PD/Rating	Equities: 0.03-0.15% (AAA – BB+) Bonds: 0.03-0.15% (AA+ – BBB-)
LGD	Equities: 1 (FRTB requirement) Bonds: 1 (FRTB requirement)